Who Has Skills in Trading Options?*

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Abstract

This paper uses account-level transaction data in Korea's index options and futures to examine option trading skills by different types of investors. We first investigate how common option trading strategies are used. We find that (i) retail investors, both domestic and foreign, are more likely to hold naked option positions, while institutional investors are more likely to use complicated strategies; (ii) volatility trading is used more often than the other classic options strategies; (iii) a small number of accounts, both institutional and retail, generate large volumes of trades using sophisticated and well hedged positions. Then we examine the association between trading strategies and account performance. Our results show that (i) foreign investors are similar to domestic investors; (ii) for both retail and institutional investors, those using volatility and sophisticated strategies outperform their peers, and those using naked options underperform; (iii) volatility traders mainly gain from selling volatilities although subject to large downside risk. Our findings suggest that skilled options traders use volatility and complicated strategies, but informational advantage and country domicile are less important.

Keywords: *Options, Institutional investors, Retail investors, Trading skills, Volatility*

1. Introduction

What do investors commonly use options for: hedging, directional speculation, or volatility trading? How do institutional and retail option investors trade? And who are skilled options investors? These questions are important for researchers, investors and policy makers who want to gain a better understanding of the functions of derivatives markets. We answer them in this study by examining Korea's index options and futures markets, where both institutional and retail investors, as well as domestic and foreign investors, actively participate in trading.

Although trading volumes in options markets have been growing for decades, actual trading patterns and the motivations of different types of investors for trading options are not clearly identified largely due to data limitation and complexity of options trading. Unlike a simple long or short position in stocks to gain directional risk exposure, options can be used to hedge underlying price changes or volatility risk, and to speculate or trade on information about future price movements or future volatility of the underlying security. Finance textbooks (e.g. Hull, 2018) describe many popular options trading strategies. However, with limited evidence in the literature, we know little about how options are used in reality by different investors. Most publicly available option datasets only provide aggregate daily volume and open interest, not separated by investor type. Therefore, it is impossible to study options trading skills using these data.

This study provides detailed descriptions of the derivatives usage of institutions and retail investors at the account level. We use a complete dataset of intraday transactions at the account level, for both options and futures on the same underlying, the Korea Composite Stock Price Index or KOSPI 200, which is the representative stock market index of South Korea, similar to the S&P 500 index in the United States. During our sample period between

2010 and 2014, the average daily options premium of KOSPI 200 options reaches the equivalent of 1 billion USD, comparable to the whole index options market in the U.S. at the same time. Our investigation also benefits from detailed account information separating institutional and retail investors, as well as domestic and foreign investors.

Our analyses reveal several interesting patterns. First of all, we find a significant difference in strategy complexity between retail and institutional investors. About two thirds of retail investors trade only options but not futures during the whole sample period. The pattern reverses for institutional investors, as only one third of them trade options exclusively. The result holds for both domestic and foreign investors. Moreover, concentrated bets of naked long or short positions in only call or put options are the most common among both domestic and foreign retail investors, accounting for about 50% of the account-days for this class of investors. Institutional investors, on the contrary, are more likely to use complicated strategies involving multiple option positions in their portfolios together with futures. Nonetheless, 21.3% of domestic institutional positions and 11% of foreign institutional positions are also concentrated naked option positions.

Second, we show that investors' usage of options for volatility trading is significantly larger than previous literature suggests. At least 16.5% of all account-days with non-zero end-of-day positions in options hold options as part of volatility trading strategies, including straddles, strangles, and butterflies. On average, their positions account for 14.5% of the end-of-day total market open interest. These numbers represent lower bounds, as we are not able to identify all instances of volatility trading in the sample. Overall, we find significant evidence of the important role of options as instruments for trading on or hedging underlying volatility. While this result differs from the conclusion of Lakonishok et al. (2007), it is in line with the conventional wisdom that options trading is often motivated by volatilities. All investor classes in our sample trade on volatilities. In fact, volatility trading is more popular among retail investors than institutional investors, as over 16% of retail positions are identified as volatility positions and this ratio is only 11.1% for domestic institutions and 4.03% for foreign institutions. The other common options trading strategies in finance textbooks, however, are not commonly used. Covered calls and protective puts together account for only 1% of total account-days and option spreads appear 3.68% of the time.

Third, a small fraction of accounts holds a significant amount of open interest in our data. This is mainly due to institutional investors' use of combinations of options and futures and complicated options-only strategies. Surprisingly, some retail investors also use such complicated strategies. We estimate that retail investors have such well hedged positions in 2%-21% of their account-day observations, representing 11.1% to 54.5% of market open interest on average. These retail investors obviously trade more than their peers and they trade more like institutional investors.

After documenting detailed options market activities at the account level, we then examine options trading performance of different types of accounts. To do so, we categorize each account by its dominating position type into day trader, naked options trader, volatility trader, and market maker with well hedged positions. If an account frequently changes trading strategies or uses complicated strategies that we are unable to identify, the account becomes unclassified and serves as the benchmark case in our performance analysis. We also look at the four account classes of domestic retail, foreign retail, domestic institution, and foreign institution. Moreover, we interact trading strategy dummies and investor classes to examine the conditional effect in our multivariate regression analysis of the aggregate account profit.

We first examine the effects of investor class and trading strategies separately. We find that, not surprisingly, institutional investors outperform retail investors on average, and foreign investors seem to outperform local investors. These results are largely consistent with the literature on underperformance of retail investors as in e.g., Odean (1999) and Barber and Odean (2000), and outperformance of foreign investors as in Grinblatt and Keloharju (2000). When we look at trading strategies, we find that day traders and naked options traders underperform the other types of traders. The worst performance comes from the group with most retail traders, the naked options traders. Volatility traders and market makers using well hedged strategies perform better.

Next, we examine the conditional effects of investor classes and trading strategies by interacting them. The results can be summarized as follows. First, the effects from investor classes are all greatly reduced, while the effects from option strategies remain similar in magnitude, if not stronger. Second, while retail investors still have the worst performance, those using volatility and sophisticated strategies perform much better than their peers, and the performance gap between retail and institutional investors is narrowest for these two types of strategies. Third, institutional day traders and naked options traders perform better than their retail peers. However, they are still net losers and trail the other institutional investors by far. In summary, we find that the bottom option investors underperform mainly because of their use of unsophisticated options trading strategies, while the top option investors outperform by mastering skills in trading volatilities and using sophisticated strategies.

Furthermore, when we examine the relation between account profitability and exposure to options Greeks, we find that both long and short delta exposure is related to lower profitability. Long vega exposure is also negatively related to account profitability, while short vega exposure is significantly positively related to performance. These results support our conclusion that directional bets on underlying price changes (strategies with high delta exposure) lead to lower profitability, while volatility trading strategies (strategies with high vega exposure) contribute to higher profitability. Volatility traders mainly gain from selling vega, but not from buying vega. While selling vega is a popular strategy among practitioners, there is still debate about the source of such profitability in academia. The profitability essentially means that the volatility implied by options is higher than the actual volatility, and that options are priced higher in reality than in classic models such as Black and Scholes (1973) and Merton (1973). On the one hand, a higher price for volatilities is consistent with the risk premium for stochastic volatilities embedded in derivatives contracts (Carr and Wu (2009), Bollerslev, Tauchen, and Zhou (2009)). On the other hand, it can also be a result of mispricing of volatilities (Goyal and Saretto (2009)). We show evidence that the profits of all volatility traders are significantly more negatively skewed compared to the profits of other investors, suggesting that volatility traders are exposed to extreme downside risk. Similar to selling insurance, short vega strategies profit most of the time from collecting premiums, but once in a while incur a large loss. Therefore, our results are more consistent with the risk premium explanation rather than mispricing.

As an additional robustness check, we conduct an out-of-sample test to see whether the performance of different types of investors is persistent. Our results show that it is. All volatility and sophisticated traders have positive excess profitability on average, while retail naked options traders have negative excess profitability on average, both in-sample and out-of-sample. Although institutional naked options traders have positive average excess profitability, it is much lower than that of institutional volatility and sophisticated traders.

Our contributions to the finance literature are mainly threefold. We are the first to document detailed account level activity in the options and underlying markets. The only study from the US market that provides stylized facts about the options trading activity of several types of investors is by Lakonishok et al. (2007). They use data on equity options daily open interest and volume for three categories of investors: firm proprietary traders, customers of full-service brokers, and customers of discount brokers. However, their data does not represent the whole US options market, as it only contains options listed on the Chicago Board Options Exchange (CBOE). Moreover, it consists of only aggregate daily volume and open interest for each option contract by investor type. Given the complexity of options strategies, it is challenging to identify trading motivations and actual strategies without account level data. For example, two retail investors holding bull and bear spreads respectively can be misclassified as a volatility investor at the aggregate level. Lakonishok et al. complement their main analysis using a small sample of options transactions from retail accounts at a discount brokerage house, but it is not representative of all investors. While Lakonishok et al. infer that volatility trading accounts for less than 3% of options market activity, we show that it is more common with a lower bound estimate above 16.5% at the account-day level. The most common strategies identified by Lakonishok et al., covered calls and protective puts, on the contrary, account for less than 1% of observations in our data. While our results are derived from the Korean market, we do find similar pattern on foreign investors in our sample.

By comparing the trading strategies and profitability of different classes of investors, we also contribute to the literature on the characteristics of institutional versus retail traders. Institutions are generally regarded as sophisticated informed investors, while retail traders are believed to be uninformed noisy traders who commit systematic mistakes. Barber et al. (2009) use data from the Taiwanese stock market to measure traders' aggregate portfolio performance and find that retail trading results in large systematic losses, while institutions profit from their trades. Kuo, Lin, Zhao (2015, 2018) study individual futures investors and show that investors with lower cognitive abilities, as well as investors who exhibit stronger herding behaviour, incur larger losses. However, more recent papers using stock market data suggest that retail traders are informed. Kaniel, Saar, and Titman (2008), Kelley and Tetlock

(2013), Barrot, Kaniel and Sraer (2016), and Boehmer, Jones and Zhang (2017) show that aggregate trading by retail investors can predict future stock returns. When it comes to trading derivatives, the literature often finds that retail investors incur losses, but Bauer, Cosemans and Eichholtz (2009) uncover a small subgroup of sophisticated retail option traders who are able to outperform consistently. However, it is not clear which option trading strategies they use to achieve their superior performance. We answer the question by showing that a subset of retail investors are skilled in using volatility trading strategies or well hedged complicated positions, which has not been documented in the literature.

We also contribute to a strand of literature that studies options' role as instruments for trading on information about underlying volatility. Ni, Pan and Poteshman (2008) report evidence consistent with such trading. They construct a measure of non-market-maker net demand for volatility from the trading volume of equity options and show that it predicts future realized volatility of the underlying stocks. Ryu and Yang (2018) find that overall demand for options in the KOSPI 200 options market does not predict underlying market volatility, but foreign investors' vega-weighted net demand for volatility does convey significant information about future volatility. Chang, Hsieh and Wang (2008) investigate whether volatility information exists in the Taiwanese option markets. They find that overall option volume is slightly informative about future realized volatility of the underlying index, while strangle combination trades show significant prediction for future volatility. Individual investors' total options trading volume and their strangle trades contain volatility information, and foreign institutional investors' options/futures combination trades are also informative. Chang, Hsieh and Wang (2010) follow the approach of Ni, Pan, Poteshman (2008), using vega-weighted net demand for volatility to detect volatility information trading in the Taiwanese options market. They show that foreign institutional investors possess the strongest volatility information, realized by delta-neutral trades. Also a few retail investors appear to be informed, and trade on volatility information using strangles. These papers focus on the information content and predictive power of options trading volume for future volatility. It is an indirect way of showing that there is volatility trading in options markets. Our paper aims to provide direct evidence that volatility trading constitutes a significant part of options usage, by analysing account-level positions in options rather than aggregate trading volume.

Related to our study, Bauer, Cosemans and Eichholtz (2009) uses account-level data from a discount broker in the Netherlands to examine individual investors' trading in equity and options. They argue that most retail investors incur losses from trading options due to poor market timing, high trading costs, and gambling and entertainment as motivations for trading. However, these results are based on opening trades only, hence do not reflect option traders' whole positions. An earlier study by Chaput and Ederington (2003) analyses large trades in options on Eurodollar futures, and finds that the most heavily traded combinations in their data are volatility strategies such as straddles and strangles. There are also several studies from countries where trading of standard option strategies takes place in a special strategy trade facility operating together with the electronic limit order book. Such facilities allow for the simultaneous execution of the multiple legs of an option strategy, thus minimizing execution risk. Flint, Lepone, and Yang (2014) use a small sample of options traded on the Australian Options Market with flags for whether a trade is part of a strategy or not, but their data is not account-level, and the lack of trade direction and quotes information requires the authors to estimate them. Fahlenbrach and Sandas (2010) look at trading in option strategies formed with FTSE-100 index options on the London International Financial Futures Exchange (Liffe). They find that, out of the options-only strategies in their sample, the most common are bull or bear spreads, followed by strangles, calendar spreads, straddles, and other strategies. They conclude that option strategies are used by both traders with volatility information and uninformed speculators chasing trends. However, their paper focuses on the information content of order flow in option strategies and does not look at end-of-day positions held by option investors. They also do not compare the different types of investors.

Other studies apart from ours have used KOSPI 200 derivatives data to study different aspects of options and futures trading, but none of them have looked at the strategies that option investors use. An exception are some articles that examine day traders, such as Ryu (2012). He finds that domestic retail accounts constitute the largest portion of total day trading activity in KOSPI 200 futures but incur substantial losses, while domestic money managers and foreign institutions constitute a smaller portion of total day trading activity but tend to profit from it. Another article that also investigates the performance of futures day traders is by Kuo and Lin (2013). They study individual day traders in the Taiwanese futures market and show that they incur significant losses.

The rest of the paper proceeds as follows. Section 2 provides details about the KOSPI 200 derivatives markets and summary statistics of our data. Section 3 describes the various strategies used by option position holders. Section 4 analyses the profitability of the different types of investors and strategies. Section 5 concludes the paper.

2. Description of the KOSPI 200 derivatives markets and the data

We use detailed data of all account-level transactions executed in Korea's main derivatives markets, the KOSPI 200 index options and futures markets, in the period from 1 January 2010 to 30 June 2014. The options and futures contracts are based on the underlying KOSPI 200 index, which consists of the 200 largest companies listed on the Korea Exchange (KRX), thus representing Korea’s overall stock market, similarly to the S&P 500 index in the US.

The KOSPI 200 options and futures attract both domestic and foreign investors globally, and have become some of the world's most actively traded and liquid derivatives instruments.

The KOSPI 200 options and futures markets are order-driven and do not need to rely on designated market makers for the provision of liquidity. Orders submitted by investors are collected in a central electronic limit order book (CLOB) and are executed according to price and time priority rules. The daily continuous trading session opens at 9:00 and closes at 15:05.[2] There is a pre-opening batch auction from 8:00 to 9:00 and a post-market batch auction from 15:05 to 15:15, when all submitted orders are first accumulated in the CLOB and then executed at a single market price at the end of the sessions. The contract size for futures is KRW 500,000. For options, it is KRW 100,000 for contracts that mature in or before June 2012, and changes to KRW 500,000 for contracts that mature after June 2012, to match the futures contracts multiplier. For each contract, the minimum tick size is 0.05 points.

Our data consists of trades with a millisecond time stamp and detailed information about both counterparties to each transaction, including account numbers, bid and ask order submission times, country codes, and investor types. Any contracts that start being traded in 2009 are excluded from the sample, since our transactions data starts from 2010. Table 1 reports aggregate summary statistics. Panel A describes the options data, and Panel B describes the futures data. We report statistics for the number of transactions, trading volume (number of contracts traded), volume-weighted options premium or futures trade price, and $volume in billions of KRW (equal to options premium or futures trade price multiplied by

[2] There are some exceptions to the normal trading hours. On the first trading day of the calendar year, the opening of the continuous trading session is delayed by one hour, to 10:00. In addition, each year in November, on the day of the Korean national College Scholastic Ability Test (CSAT) for college entrance, the opening and closing of the continuous trading session are delayed by one hour, from 10:00 to 16:05.

trading volume and contract size). First, we calculate total number of transactions, trading volume, $volume, and volume-weighted average premium or trade price for each day. Then, we calculate the mean, standard deviation, minimum, median, maximum, and total sum of these variables across all days in the sample.

[Table 1 about here]

During our sample period, the total trading volume in KOSPI 200 derivatives is approximately 8.6 billion option contracts and 217.5 million futures contracts traded. These correspond to options and futures dollar volumes of KRW 1,323,552 billion and KRW 27,928,474 billion, respectively, or approximately USD 1,173 billion and USD 24,756 billion. Such numbers are comparable to the total trading volumes observed in the US derivatives markets and testify to the high liquidity of the Korean markets.

The sub-panels in Table 1 contain summary statistics for different sub-samples. As expected, most trading activity takes place during normal trading hours, which refer to the daily continuous trading session from 9:00 to 15:05. Trading volume in call options is slightly higher than that in put options. Moneyness of a call (put) option is defined by the ratio of the underlying spot price (strike price) to the strike price (underlying spot price). An option is out of the money (OTM) / at the money (ATM) / in the money (ITM) if its moneyness is less than 0.95 / between 0.95 and 1.05 / greater than 1.05. ATM options are most actively traded, followed by OTM options, while ITM options attract little trading volume. Contracts that are closer to maturity are more actively traded.

Table 2 reports the total number of investor accounts that trade at least once during our sample period. It also reports the number of accounts that trade options at least once in the data, and these are further separated into accounts that trade only options and accounts that trade both options and futures. Table 2 also reports the number of accounts by investor class. We use the country codes to separate accounts into domestic (Korean) and foreign accounts, and we use the investor type codes to separate them into retail investors and institutions (which include financial investment companies, banks, pension funds, insurance companies, trusts, state and local government institutions, and other institutions). Based on these categories, we assign a unique class to each account: Domestic Institution, Foreign Institution, Domestic Retail, or Foreign Retail.

[Table 2 about here]

In total, there are 187,323 trading accounts in our data, of which 161,010 are option traders. Most accounts are domestic retail investors, of which two thirds trade only options, and the remaining one third trade both options and futures. On the other hand, only one third of institutional accounts trade options exclusively, while the majority of them trade both options and futures. Although most of the accounts in the data are domestic investors, Table 3 shows that foreign institutions generate a large portion of options trading volume. The table provides summary statistics of the options trading activity of the different account classes. We use the bid and ask markers in the data to mark which transaction counterparty is the buyer and which is the seller. We compare the bid and ask order submission times and mark the investor who submitted their order first as the liquidity provider and the investor whose order matched the first one as the trade initiator (or aggressor). Panel A contains summary statistics by trade initiator class, and Panel B by liquidity provider class. There are some transactions where the two orders cross at the same time, hence the trade initiator and liquidity provider cannot be identified. Those observations are not included in the results in Table 3. The table shows that, on an average day, foreign institutions initiate the largest number of transactions and generate the greatest trading volume of all investor classes. On the other hand, domestic institutions and domestic retail investors tend to act as liquidity providers. Foreign retail investors execute only a small portion of all trades.

[Table 3 about here]

3. Strategies of option position holders

In order to study the different trading strategies that option investors use, we first separate accounts into day traders and position holders. Accounts that never hold a position in options at the end of the trading day are categorized as day traders. For the remaining accounts, we use the transactions data to construct the end-of-day positions held by each account in each different contract. For each account, day and contract, the end-of-day position is equal to the previous day's position plus any purchased lots minus any sold lots. Then, we can study the combinations of different contracts that each account-day holds and extract the corresponding strategies.

Table 4 reports account-day results for option position holders' strategies, grouped into five main categories. Combinations of options and futures include covered calls, protective puts, and any other combinations. Naked options in one type of position only refer to positions in long calls only, or short calls only, or long puts only, or short puts only. They are not accompanied by any position in futures contracts. Volatility trading strategies include straddles, strangles, and butterflies. These are strategies used by investors who want to trade on information about underlying volatility or to hedge volatility risk. Spreads include strategies that use options to create synthetic stocks, bull spreads, bear spreads, and calendar spreads. Finally, the category of other strategies consists of any combinations of option contracts which do not fall into the above categories. For each strategy category, we report the number of account-days that hold a position corresponding to the strategy, as a percentage of all account-days with a non-zero end-of-day position in options. We also report the average percentage of open interest: for each strategy, first we calculate the end-of-day number of options held by all investors who use that strategy, as a percentage of the total number of options held in the market by all investors (overall open interest), and then we take the time-series average. The open interest percentages sum to a total of 200% since each option contract is held simultaneously by two counterparties – each long position has a corresponding short position. The table contains results for all account-days aggregated, as well as for each investor class separately.

The results in Table 4 show that options are used for volatility trading more widely than Lakonishok et al. (2007) suggest. 16.5% of all account-days hold options as part of a volatility trading strategy. On average, positions in these strategies account for 14.5% of the overall market end-of-day open interest. It must be noted that these numbers represent a lower bound for volatility trading, as we are not able to identify all volatility trading strategies in the data, and it is likely that some of them are part of the category of other strategies. We discuss this in more detail in Section 3.3. Examining the usage of volatility trading strategies by the different investor classes reveals that they are popular with all investors. 11% of domestic institution account-days and 4% of foreign institution account-days hold positions as part of volatility trading strategies, although on average their positions account for a small percentage of open interest. About 17% of both domestic and foreign retail account-days hold volatility trading positions. The positions of domestic retail volatility traders account for about 11% of total open interest on an average day. These numbers show that volatility trading is a significant determinant of options trading.

[Table 4 about here]

A surprisingly large percentage of account-days hold positions in one type of naked options only. We define naked options as positions in options that are not combined with any positions in futures. Hence, these options do not hedge any market exposure from futures contracts. This leads us to conclude that options are widely used for one-directional speculative trading. This result is in line with Lakonishok et al. (2007) who also conclude that hedging directional price changes of the underlying security by non-market-makers drives only a small part of option market activity. They base this conclusion on the holdings of a small sample of retail accounts. Indeed, when we examine the break-down of our results by investor class, we can see that about 50% of retail account-days hold naked options positions, which accounts for about 13% of total end-of-day open interest on average. Although this type of speculative strategy is also used by 21% of domestic institution account-days and 11% of foreign institution account-days, they each account for less than 1% of open interest on average. Naked options strategies are further examined in Section 3.2.

Spreads do not seem to be widely used by option position holders. Only 3.7% of account-days hold spreads, and their positions account for less than 6% of open interest on average. For this reason, we do not examine these account-days further.

Combinations of options and futures account for 88.7% of total option market open interest on average and are predominantly used by institutions. We examine these strategies in more depth in Section 3.1.

The remaining category of other option strategies accounts for an average of 76.3% of open interest. The large holdings in options-and-futures combinations and other strategies point to a possible use of such strategies by accounts who act as market makers. We explore this possibility further in Section 3.4.

3.1. Combinations of options and futures

This section focuses on the strategies that option traders create in combination with futures. We extract these by checking the type of options and futures exposure that an account-day has: long calls, short calls, long puts, short puts, long futures, or short futures. Well-known combinations include covered calls and protective puts. Long covered calls consist of long calls and short futures, while short covered calls consist of short calls and long futures. Long protective puts are created with long puts and long futures, while short protective puts are created with short puts and short futures. Table 5 breaks down the category of options-and-futures combinations into these four strategies, as well as a remaining category of any other combinations. We can see that covered calls and protective puts are rarely used. On the other hand, the category of other combinations constitutes 60% of foreign institutions account-days, 22% of domestic institutions account-days, and about 5% of retail account-days. In total, their positions account for an average of 87.5% of overall market open interest. In Section 3.4, we further explore the possibility that this category of other options-and-futures combinations includes well hedged positions of market makers.

[Table 5 about here]

3.2. Naked options in one type of position only

In this section, we take a closer look at naked options in one type of position only. We include here account-days which hold naked positions in either long calls only, or short calls only, or long puts only, or short puts only. These are one-directional exposures which are not combined with any positions in futures contracts. We do not have data on investors' equity trades, so we cannot be certain that the options positions are not used for hedging a stock portfolio. However, it is unlikely that index options are used for hedging individual stocks, as this would imply that the investor is holding all 200 stocks that constitute the KOSPI 200 index. Otherwise, if an investor holds only a few stocks, it would make more sense for him to hedge with single stock options rather than index options. Therefore, we argue that these naked options positions are more likely to be speculative strategies rather than hedges of the underlying index. This assumption is supported by the findings of Lakonishok et al. (2007) and Bauer, Cosemans, Eichholtz (2009).

Table 6 shows that 30% of account-days hold naked positions in long calls only and 21% of account-days hold naked positions in long puts only. These long exposures also represent the largest percentages of total market open interest at the end of the day, compared to the short exposures. Naked short call and short put exposures are much less common. These results are driven by the retail investors in the sample. Our results differ somewhat from the analyses of Lakonishok et al. (2007) about one-directional holdings. They find that, in aggregate, long call and short call positions are most common, while we find that long call and long put exposures are most common.

[Table 6 about here]

The results in Table 6 may be taken as evidence that retail traders often use options to engage in one-directional speculative trading on future price changes of the underlying index. It seems that some institutions also engage in this type of trading, but much less than retail investors do.

3.3. Volatility trading

Now we turn to the volatility trading strategies. Table 7 presents details about the different strategies that option position holders use to trade on underlying volatility. First, we extract long and short straddles and strangles created by taking a position in two different option contracts only. Long (short) straddles are created by combining long (short) calls and long (short) puts with the same strike price and maturity date. Long (short) strangles are created with long (short) calls and long (short) puts with the same maturity date but different strike prices. Next, we would like to extract account-days that use more than two different option contracts to create combinations of straddles and strangles. Regardless of how many different option contracts an account-day uses, we check the types of exposures they have. If they hold long calls and long puts only, we can be sure that they are using a combination of long straddles and/or long strangles. If they hold short calls and short puts only, then they are using a combination of short straddles and/or short strangles. In Table 7 we report these strategies as "long combinations" and "short combinations". Finally, we extract butterflies created with three different option contracts. A call (put) butterfly spread is a strategy that combines three call (put) contracts with different strike prices, such that the option contract with the middle strike price has twice the number of lots invested in it, compared to the number of lots invested in the other two option contracts. For example, a long call butterfly can be created by buying one lot in a call option contract with the lowest strike price, selling two lots in a call option contract with the middle strike price, and buying one lot in a call option contract with the highest strike price. We must note that we are only able to identify butterfly spreads created using three different option contracts, but we are unable to extract any combinations of butterflies created using six, nine, or more different option contracts, because we cannot be sure that they are not other strategies. Similarly, some combinations of long and short straddles and strangles may be left in the category of other strategies, because we cannot say for sure what type of strategy is used by an account that holds a large number of different option contracts. Therefore, the numbers presented in Table 7 are lower bounds, and the usage of options for volatility trading may in fact be larger.

[Table 7 about here]

Table 7 shows that at least 16.5% of all account-days engage in volatility trading, and their positions represent on average 14.5% of the total market open interest at the end of the day. Strangles are much more commonly used than straddles and butterflies. We also observe that about half of volatility trading strategies consist of combinations of straddles and/or strangles (using more than two different option contracts). Interestingly, more retail account-days hold positions as part of volatility trading strategies, compared to the institutional account-days. An exception to this is the 7% of domestic institutions that use combinations of short straddles and/or strangles. Butterflies, on the other hand, do not seem to be a popular strategy among any of the investor classes.

To be sure that we have accurately identified volatility trading strategies, we calculate the exposure of each account's end-of-day position to the greeks. We focus on delta which measures the exposure of an option position to changes in the underlying price, and vega which measures the option position's sensitivity to changes in the underlying volatility. Hence, we should expect that volatility traders have low delta exposure and high vega exposure. We scale end-of-day delta and vega exposure by the number of lots held by the account on that day. As expected, all the identified strategies in Table 7 have a low average scaled delta, and a high average scaled vega in absolute terms. The long volatility strategies have an average scaled delta of 0.01 and an average scaled vega of 0.11, while the short volatility strategies have an average scaled delta of -0.02 and an average scaled vega of -0.16.

Overall, we find evidence that investors' usage of options for volatility trading is significantly larger than previously identified in the literature. This points to an important use of options as instruments for trading on or hedging underlying volatility, and not solely for speculating on or hedging underlying price changes.

3.4. Market makers

The KOSPI 200 options market is order-driven and does not rely on designated market makers for the provision of liquidity. Nevertheless, we would expect that some accounts act as market makers and profit by providing liquidity to other traders in the market. In this section, we attempt to identify account-days whose behavior resembles that of market makers. This will be helpful in the following analyses of the profitability of different options trading strategies. We start by collecting account-days which have remained without an assigned strategy. These include the account-days holding combinations of options and futures other than covered calls and protective puts (reported as "other combinations" in the last row of Table 5). They also include account-days holding only options, whose strategies do not include naked options, volatility trading, or spreads (reported as "other strategies" in the last row of Table 4). From these, we exclude any positions which may be used to achieve a calendar exposure (combinations of options with different maturities). We are left with complex strategies using more than two different option contracts, with more than two different exposures out of the four possible ones: long calls, short calls, long puts, and short puts. Hence, we identify a set of account-days which we refer to as possible market makers, reported in the first row of Table 8. They represent 22% of all account-days with non-zero positions in options, and on average 164% of total open interest. These numbers seem quite high, and as mentioned in the previous section, we can expect that some of these account-days are volatility traders. In order to separate the market makers from the volatility traders, we impose artificial cut-offs on the greeks exposure of these account-days. Unlike volatility traders, market makers are expected to have a low end-of-day position exposure to both delta and vega. We calculate the 50th and the bottom 25th percentiles of absolute scaled delta exposure and absolute scaled vega exposure of this sub-sample of possible market makers. Those account-days that are in both the bottom delta percentile and the bottom vega percentile are categorized as market makers. Table 8 reports the results for both cases when we use 50% and 25% as the cut-off. Using the 25% cut-off seems to be too low, as we are left with account-days which hold on average only 38% of the overall market open interest. Hence, for any further analyses, we choose to use the 50% cut-off. It leaves us with about 7% of account-days identified as market makers. Their positions account for 77% of total open interest on average. We want to be sure that there is a significant difference between the greeks exposure of this group of market makers and the rest of the accounts in the broader category "possible market makers" (which likely includes volatility traders). So, we calculate average absolute delta and vega by first averaging the absolute greeks across accounts and then averaging across days. The bottom 50% market makers have an average absolute delta of 0.01 and an average absolute vega of 0.01, while the rest of the "possible market makers" have an average absolute delta of 0.14 and an average absolute vega of 0.09.

[Table 8 about here]

Although our strategy for identifying market makers is not perfect, we believe that we are able to identify a large portion of account-days which are likely to act as market makers. These are account-days that hold complex combinations of multiple different contracts, which do not correspond to any other trading strategy, and have low delta and vega exposure. We can see from the table that the identified market makers include account-days from all four investor classes.

4. Profitability of option traders

After discovering the most commonly used option strategies, we would like to know which of them are most profitable and which types of investors outperform the rest. For each investor account, we use the transactions records to calculate the total cumulative profit and loss (P&L) over the whole sample period. Hence, our measure of account profitability is the dollar amount generated by all trades that the account has executed from January 2010 to June 2014. If there are any positions that are not closed before the end of our sample period, we mark them to market based on the closing value of the underlying index on the last trading day in our sample (30 June 2014). Later on, in our regression analyses, we use a logarithm transformation of account P&L as the dependent variable.

In order to examine the relation between total account profitability and type of strategy used, we need to label each account as day trader, naked options trader, volatility trader, market maker, or other. We have already defined day traders as accounts who never hold a position at the end of the trading day. However, we observe that accounts which are position holders may hold different strategies on different days throughout the sample period. For this reason, we define an account as a naked options trader only if he holds naked options positions on at least 50% of the days when he holds any non-zero position in options. Similarly, we mark an account as a volatility trader (market maker) if he holds positions that correspond to a volatility trading (market making) strategy at least 50% of all days when he holds any options position. The remaining category labelled as "others" consists of accounts that engage in other options strategies most of the time, accounts that use several different strategies without having a predominant one, and accounts that trade only futures but not options. Table 9 reports the number of accounts for each strategy and each investor class, as well as the percentage of total trading volume over the sample period that the group has generated.

[Table 9 about here]

About 7% of all accounts are day traders who never hold end-of-day positions in options. Together, they generate 10% of total sample trading volume. Roughly 9% of domestic institutions, 5% of foreign institutions, 7% of domestic retail investors, and 8% of foreign retail investors are day traders.

Around 55% of all accounts are classified as naked options traders. This closely matches Table 4 which showed that 55.7% of all account-days hold positions in naked options. These accounts generate 38% of total trading volume. By investor class, only a few institutions are naked options traders (8% of domestic institutions and 10% of foreign institutions), but a large portion of retail investors predominantly use such one-directional trading strategies (60% of domestic retail and 48% of foreign retail accounts).

Approximately 5.5% of all accounts are volatility traders, and their trading activity accounts for 5% of total trading volume over the sample period. Approximately 2% of domestic institutions, 1% of foreign institutions, 6% of domestic retail investors, and 7% of foreign retail investors are volatility traders. Although the volume percentages are low, it must be noted that even if an account executes few trades, he may hold the corresponding positions for a long time. In comparison, we saw in Table 4 that 16.5% of account-days hold positions that are part of volatility trading strategies.

Finally, 2.6% of accounts are identified as investors who regularly act as market makers. By investor class, they are about 4% of domestic institutions, 6.5% of foreign institutions, 2.5% of domestic retail investors, and 5% of foreign retail investors. The rest of the accounts are in the category "others".

Table 10 presents regression analyses of the relation between profitability and investor types. We would like to understand which class of investors and which option trading strategies outperform others on average. We perform four account-level regression analyses. The dependent variable in all of them is the logarithmic transformation of account P&L. If an account has generated a positive profit over the sample period, we calculate *log(1+P&L)*. If an account has generated a loss instead, we calculate *log(1/(1– P&L))*. The table contains the estimated regression coefficients and below them the corresponding t-statistics in parentheses.

[Table 10 about here]

The independent variables in the first regression are three dummy variables for the three investor classes: foreign retail, domestic institution, and foreign institution. Since all the remaining accounts are domestic retail, the intercept represents that class of investors. We can see that, on average, institutions generate positive profits, while retail accounts incur losses. Foreign investors tend to outperform domestic investors. The second regression uses as independent variables four dummies for the four types of option traders we identified: day traders, naked option traders, volatility traders, and market makers. All coefficients are statistically significant and show that on average naked options traders generate the largest losses, while market makers generate the largest gains. Volatility traders slightly outperform other traders, while day traders slightly underperform on average.

What we are more interested in, however, are the interaction effects between the account classes and strategy dummies. Different classes of investors have different characteristics, such as capital constraints, transaction costs, and other trading barriers. Thus, different strategies may be suited to different types of traders. We would like to know if a particular strategy brings superior profits to a particular class of investors. The third regression shows that foreign retail volatility traders significantly outperform other accounts and generate a positive profit on average. The coefficient on the "volatility trader" dummy, which corresponds to domestic retail volatility traders, is also positive and statistically significant. This suggests that volatility trading is a profitable strategy for a subset of retail option investors. Institutional volatility traders also generate positive profits on average, although the coefficients on their interaction variables are not statistically significant. The results also show that naked options traders incur large losses on average, although institutional naked options traders incur much smaller losses than retail naked options traders. Market making, on the other hand, is profitable for all investor classes, especially foreign accounts. Finally, day trading seems to be unprofitable for retail investors on average, although the coefficients on their interaction variables are not significant. Institutional day traders, especially the foreign ones, seem to be able to outperform other accounts.

The last regression adds control variables for account activity. They are meant to mitigate concerns about the possibility that profits are generated by the largest accounts simply because they have the capacity to trade more. We calculate each account's total trading volume generated over the whole sample period (all the trades that he executed in order to generate his cumulative P&L), as well as the number of days in the sample when the account was active (the number of days when he traded options or futures at least once). We take the logarithms of these variables. Their coefficients in the fourth regression are negative and significant, while other variables become more positively significant compared to the third regression. This suggests that excessive trading is detrimental to investors' profitability.

Another way to test which type of strategies are more profitable is to examine the relation between account profitability and exposure to the greeks. We calculate each account's end-of-day delta and vega exposure, scaled by the number of lots held by the account on that day. Then, we take the time-series average of the account's long delta exposure, absolute short delta exposure, long vega exposure, and absolute short vega exposure. Long delta (or positive delta) positions, such as long calls or short puts, represent directional bets on an increase in the underlying price. Short delta (or negative delta) positions, such as short calls or long puts, represent directional bets on a decrease in the underlying price. Long vega (or positive vega) positions, such as long straddles or long strangles, represent bets on an increase in underlying volatility, and therefore profit when the underlying price experiences large moves in either direction. Short vega (or negative vega) positions, such as short straddles or short strangles, represent neutral strategies where the trader believes that the underlying price will not move significantly in either direction. The maximum profit from strategies that sell vega is equal to the premium collected from writing the options. We take the absolute values of short delta and short vega exposures in order to use them in regressions.

Table 11 presents the results of regressing the logarithmic transformation of account P&L (calculated in the same way as in Table 10) on average long delta and vega exposure and average absolute short delta and vega exposure, as well as the three investor class dummies used in the previous regressions in Table 10, and interaction effects between investor class and greeks exposure. Since day traders do not hold any overnight positions and therefore do not have any end-of-day greeks exposure, we exclude them from this analysis. The number of observations is further reduced because we have missing values for some accounts' exposure to the greeks (there are instances when it is not possible to estimate end-of-day delta and vega). We perform three account-level regression analyses. The first one regresses our measure of account profitability on the greeks exposure variables only. The coefficients on both average long delta exposure and average absolute short delta exposure are negative and significant. This supports our earlier argument that directional bets on underlying price changes (strategies with high delta exposure) lead to lower profitability. This holds for both bullish and bearish bets. The coefficient on average long vega exposure is also negative, while the coefficient on average absolute short vega exposure is positive and strongly significant. These results support our earlier conclusion that volatility trading strategies (strategies with high vega exposure) contribute to higher profitability, but we can see that only positions that are short vega outperform. Therefore, volatility traders gain from selling vega, but not from buying vega.

The second regression adds the three investor class dummies, as well as interaction effects between the greeks exposure variables and the investor class dummies. The third regression also adds control variables for account activity: logarithm of total account trading volume and logarithm of account active days (calculated in the same way as in Table 10). Both regressions show similar results. They confirm the result that only short vega positions generate superior profits. The negative coefficients on the interaction variables, which are often not statistically significant, suggest that institutions and foreign retail investors are not better than domestic retail investors in selling vega.

[Table 11 about here]

If selling volatility provides superior performance, why are short volatility strategies not used by more investors? Even though we find that volatility trading is more widespread than previously thought, it still accounts for only a portion of total option market activity. Our next analysis aims to explain the reason. Short vega strategies, such as short straddles or short strangles, consist of writing options and represent the investor's belief that the underlying price will not move significantly in either direction over the life of the options. These strategies have a limited profit potential, equal to the premiums collected from writing the options, while the potential losses can be unlimited. Similarly to insurance sellers, vega sellers profit most of the time from collecting premiums, but once in a while incur a large loss. Table 12 shows empirical evidence of this profit pattern. The table presents regression analyses of the relation between investor types and skewness of daily, weekly, and monthly account profitability. For each account, we use the transactions records to calculate profit and loss (P&L) on daily, weekly, and monthly horizons. Hence, the measure of profitability here is the dollar amount generated by all trades that the account has executed on each day, week, or month. If there are any positions that are not closed before the end of the horizon, we mark them to market based on the closing value of the underlying index at the end of the given day, week, or month. We apply a logarithmic transformation to the calculated P&L values (in the same way as in Table 10). Then, for each account, we calculate the skewness of his daily, weekly, and monthly profitability over the sample time period. We perform three regression analyses, where the dependent variables are skewness of daily log P&L, skewness of weekly log P&L, and skewness of monthly log P&L. The independent variables in all of them are the same as in Table 10. The results in Table 12 show that regardless of the horizon used, the profits of all volatility traders are significantly more negatively skewed compared to the profits of other investors. Negative skewness describes a distribution with a longer left tail, meaning that most of the time volatility traders are profitable, but they are exposed to large downside risk.

[Table 12 about here]

As an additional robustness check, we conduct an out-of-sample test to see whether the performance of different types of investors is persistent. To do that, we split our sample into two equal subperiods. The first half of the sample, used for in-sample analysis, covers the period from 1 January 2010 to 31 Mar 2012. The second half of the sample, used for out-of-sample analysis, covers the remaining period from 1 Apr 2012 until 30 June 2014. Using trading data only from the first half of the sample, we assign to each account a strategy dummy: naked options trader, volatility trader, or market maker. We create the dummies following the same principle as in previous analyses: for example, if an account uses a volatility trading strategy at least 50% of the time in-sample (50% of the days when he holds a position in-sample), then he is marked as a volatility trader. Then, we keep the same account classification for the second half of the sample. We only keep accounts that execute transactions in both subperiods, which reduces our sample. For each account, we calculate profits generated in the two subperiods (in-sample P&L and out-of-sample P&L), and we use a logarithmic transformation of P&L (calculated in the same way as in Table 10). We calculate excess log P&L, equal to log P&L minus market average log P&L. In Table 13, we report the in-sample and out-of-sample average excess log P&L for each investor type. We can see that there is performance persistence out-of-sample – the average profitability of all investor types is very similar in the two sample subperiods. All volatility traders and market makers have positive excess profitability on average, while retail naked options traders have negative excess profitability on average, both in-sample and out-of-sample. Although institutional naked options traders have positive average excess profitability, it is much lower than the average excess profitability of institutional volatility traders and institutional market makers.

[Table 13 about here]

5. Conclusion

In this paper, we analyse a detailed account-level dataset of intraday transactions in KOSPI 200 index options and futures, in order to learn which trading strategies are commonly used by option investors. We also examine the profitability of those strategies when executed by different classes of investors. Our motivation for studying this comes from the fact that little is known about the real-world trading activities of different types of option investors, what purposes options are used for, and whether certain option strategies result in superior profits.

Our results reveal that retail investors are more likely to hold naked options for one-directional speculation, while institutional investors are more likely to use complicated strategies. A small number of accounts, both institutional and retail, generate large volumes of trades using sophisticated and well hedged positions. In addition, volatility trading is used more often than the other classic options strategies. In terms of total account profits, retail investors underperform in general, but those using volatility and sophisticated strategies outperform their peers, while those using naked options further underperform. Institutional investors outperform in general, but those using naked option positions underperform the rest. Overall, our findings suggest that skilled options traders use volatility and complicated strategies, but informational advantage and country domicile are less important. Additional analyses show that volatility traders gain from selling vega, but not from buying vega. Short volatility positions often profit from the premiums collected from writing options but are exposed to large downside risk.

Overall, our paper contributes to the literature by providing a complete description of option investors' activities. We reveal the most common motivations for trading options, the main strategies that different types of investors use, and their profitability. The results are relevant for researchers and policy makers who want to gain a better understanding of derivatives markets, as well as for investors who can draw implications about their own derivatives usage.

References

Barber, B. M., Lee, Y., Liu, Y., Odean, T. (2009). Just How Much Do Individual Investors Lose by Trading? Review of Financial Studies 22(2), 609-632.

Barber, B. M., Odean, T. (2000). Trading Is Hazardous to Your Wealth: The Common Stock Investment Performance of Individual Investors. Journal of Finance 55(2), 773-806.

Barrot, J., Kaniel, R., Sraer, D. (2016). Are retail traders compensated for providing liquidity? Journal of Financial Economics 120(1), 146-168.

Bauer, R., Cosemans, M., Eichholtz, P. (2009). Option trading and individual investor performance. Journal of Banking and Finance 33(4), 731-746.

Black, F., Scholes, M., 1973. The pricing of options and corporate liabilities. Journal of Political Economy 81(3), 637–654.

Boehmer, E., Jones, C. M., Zhang, X. (2017). Tracking Retail Investor Activity. Working Paper.

Bollerslev, T., Tauchen, G., Zhou, H. (2009). Expected stock returns and variance risk premia. Review of Financial Studies 22(11), 4463-4492.

Carr, P., Wu, L. (2009). Variance risk premiums. Review of Financial Studies 22(3), 1311-1341.

Chang, C., Hsieh, P., Wang, Y. (2010). Information content of options trading volume for future volatility: Evidence from the Taiwan options market. Journal of Banking and Finance 34(1), 174-183.

Chang, C., Hsieh, P., Wang, Y. J. (2008). Volatility Information for the Overall Options and Combination Trading Volume: Evidence of the TAIEX Options Market. Working Paper.

Chaput, J. S., Ederington, L. H. (2002). Option Spread and Combination Trading. Working Paper.

Fahlenbrach, R., Sandas, P. (2010). Does information drive trading in option strategies? Journal of Banking and Finance 34(10), 2370-2385.

Flint, A., Lepone, A., Yang, J. Y. (2014). Do option strategy traders have a disadvantage? Evidence from the Australian options market. Journal of Futures Markets 34(9), 838-852.

Goyal, A., Saretto, A. (2009). Cross-section of option returns and volatility. Journal of Financial Economics 94(2), 310-326.

Grinblatt, M., Keloharju, M. (2000). The investment behavior and performance of various investor types: a study of Finland's unique data set. Journal of Financial Economics 55(1), 43-67.

Hull, J. C. (2018). Options, Futures, and Other Derivatives, 10th Edition. Pearson.

Kaniel, R., Saar, G., Titman, S. (2008). Individual Investor Trading and Stock Returns. The Journal of Finance 63(1), 273-310.

Kelley, E. K., Tetlock, P. C. (2013). How Wise Are Crowds? Insights from Retail Orders and Stock Returns. The Journal of Finance 68(3), 1229-1265.

Kuo, W., Lin, T. (2013). Overconfident individual day traders: Evidence from the Taiwan futures market. Journal of Banking and Finance 37(9), 3548-3561.

Kuo, W., Lin, T., Zhao, J. (2015). Cognitive Limitation and Investment Performance: Evidence from Limit Order Clustering. Review of Financial Studies 28(3), 838-875.

Kuo, W., Lin, T., Zhao, J. (2018). The Correlated Trading and Investment Performance of Individual Investors. Working Paper.

Lakonishok, J., Lee, I., Pearson, N. D., Poteshman, A. M. (2007). Option Market Activity. The Review of Financial Studies 20(3), 813-857.

Merton, R. (1973). Theory of rational option pricing. Bell Journal of Economics 4(1), 141-183.

Odean, T. (1999). Do investors trade too much? The American Economic Review 89(5), 1279-1298.

Ryu, D. (2012). The profitability of day trading: An empirical study using high-quality data. Investment Analysts Journal 75, 43-54.

Ryu, D., Yang, H. (2018). Who has volatility information in the index options market? Finance Research Letters.

Table 1
Aggregate summary statistics for the options and futures data

This table reports aggregate summary statistics for our data. Panel A describes the options data; Panel B describes the futures data. All contracts are based on the underlying KOSPI 200 index. The sample time period is from 1 January 2010 to 30 June 2014. Contracts that start being traded in 2009 are excluded from the sample. We report statistics for the number of transactions, trading volume (number of contracts traded), volume-weighted options premium or futures trade price, and $volume in billions of KRW (equal to options premium or futures trade price multiplied by trading volume and contract size). First, we calculate total number of transactions, trading volume, $volume, and volume-weighted average premium or trade price for each day. Then, we calculate the mean, standard deviation, minimum, median, maximum, and total sum of these variables across all days in the sample. The contract size for futures is KRW 500,000. For options, it is KRW 100,000 for contracts that mature in or before June 2012, and changes to KRW 500,000 for contracts that mature after June 2012. The sub-panels contain summary statistics for different sub-samples. Normal trading hours refer to the daily continuous trading session from 9:00 to 15:05. Moneyness of a call (put) option is defined by the ratio of the underlying spot price (strike price) to the strike price (underlying spot price). An option is out of the money (OTM) / at the money (ATM) / in the money (ITM) if its moneyness is less than 0.95 / between 0.95 and 1.05 / greater than 1.05.

Panel A: Options data

A-1: Aggregate summary statistics for the options data

	Number of transactions	Trading volume	Premium	$volume (billions of KRW)
daily mean	905,026	7,783,991	1.14	1,197
std	505,100	7,664,950	0.47	597
min	984	4,342	0.51	1.61
median	804,878	5,054,738	1.05	1,100
max	3,360,618	42,188,606	4.33	6,277
total over the sample period	1,000,958,323	8,609,093,878		1,323,552

	Number of transactions daily mean	Trading volume daily mean	Premium daily mean	$volume (billions of KRW) total over the sample period
A-2: Summary statistics by option moneyness				
OTM	183,092	2,251,366	0.45	180,810
ATM	716,845	5,519,158	1.72	1,121,400
ITM	5,108	13,516	18.5	21,305
A-3: Summary statistics by option contract type				
Call	454,010	4,059,280	1.05	645,780
Put	451,016	3,724,711	1.30	677,770
A-4: Summary statistics by trading hours				
Normal trading hours	897,867	7,717,283	1.15	1,312,900
Outside normal trading hours	7,158	66,708	0.92	10,657
A-5: Summary statistics by time to maturity				
0-40 days to maturity	918,363	8,001,045	1.07	1,293,400
41-70 days to maturity	18,749	66,504	2.39	21,880
>70 days to maturity	2,488	10,665	4.89	8,244

Panel B: Futures data

B-1: Aggregate summary statistics for the futures data

	Number of transactions	Trading volume	Trade price	$volume (billions of KRW)
daily mean	110,926	215,543	254.8	27,679
std	61,169	122,784	15.5	15,509
min	1	1	203.1	0.10
median	110,697	211,869	256.4	27,242
max	387,316	759,318	295.4	92,362
total over the sample period	111,923,887	217,482,925		27,928,474

	Number of transactions daily mean	Trading volume daily mean	Trade price daily mean	$volume (billions of KRW) total over the sample period
B-2: Summary statistics by trading hours				
Normal trading hours	98,202	197,063	254.9	25,512,000
Outside normal trading hours	13,808	20,170	257.0	2,416,200
B-3: Summary statistics by time to maturity				
0-40 days to maturity	131,170	256,526	256.5	12,606,000
41-70 days to maturity	122,692	241,014	259.8	9,225,200
>70 days to maturity	25,004	47,197	255.5	6,097,000

Table 2
Description of investor accounts

This table reports the total number of investor accounts that trade at least once during our sample period. It also reports the number of accounts that trade options at least once in the data, and these are further separated into accounts that trade only options and accounts that trade both options and futures. We also report the number of accounts by investor class. We use the country codes in our data to separate accounts into domestic (Korean) and foreign accounts, and we use the investor type codes to separate them into retail investors and institutions (which include financial investment companies, banks, pension funds, insurance companies, trusts, state and local government institutions, and other institutions). Based on these categories, we assign a unique class to each account: Domestic Institution, Foreign Institution, Domestic Retail, or Foreign Retail. The sample time period is from 1 January 2010 to 30 June 2014.

	Number of accounts	Number of accounts that trade options	Number of accounts that trade only options	Number of accounts that trade options and futures
Total	187,323	161,010	108,122	52,888
Domestic Institutions	13,795	5,904	1,862	4,042
Foreign Institutions	1,556	667	183	484
Domestic Retail	171,274	153,835	105,682	48,153
Foreign Retail	698	604	395	209

Table 3
Summary statistics of the options trading activity of different investor classes

This table provides summary statistics of the options trading activity of the different account classes. We use the bid and ask markers in the data to mark which transaction counterparty is the buyer and which is the seller. We compare the bid and ask order submission times and mark the investor who submitted their order first as the liquidity provider and the investor whose order matched the first one as the trade initiator (or aggressor). Transactions for which the two orders cross at the same time are excluded from the results in this table, since the trade initiator and liquidity provider cannot be identified in those cases. Panel A contains summary statistics by trade initiator class, and Panel B by liquidity provider class. The sample time period is from 1 January 2010 to 30 June 2014.

	Number of transactions daily mean	**Trading volume** daily mean	**Premium** daily mean	**$volume (billions of KRW)** total over the sample period
Panel A: By trade initiator class				
Domestic Institutions	121,167	1,957,857	0.73	179,806
Foreign Institutions	505,523	3,957,154	1.31	849,309
Domestic Retail	276,995	1,854,944	1.07	292,682
Foreign Retail	1,221	13,904	0.93	1,564
Panel B: By liquidity provider class				
Domestic Institutions	197,588	2,813,749	0.74	275,061
Foreign Institutions	253,420	2,002,524	1.39	479,232
Domestic Retail	451,779	2,948,881	1.27	565,484
Foreign Retail	2,116	18,655	1.36	3,583

Table 4
Strategies of position holders

This table reports account-day results for option position holders' strategies. We define position holders as accounts that hold a position in options at the end of the trading day at least once in the sample. We use transactions data to construct the end-of-day positions held by each account in each different contract. For each account, day and contract, the end-of-day position is equal to the previous day's position plus any purchased lots minus any sold lots. Then, we study the combinations of different contracts that each account-day holds and extract the corresponding strategies. We group strategies into five main categories. Combinations of options and futures include covered calls, protective puts, and any other combinations. Naked options in one type of position only refer to positions in long calls only, or short calls only, or long puts only, or short puts only. They are not accompanied by any position in futures contracts. Volatility trading strategies include straddles, strangles, and butterflies. Spreads include bull spreads, bear spreads, synthetic stocks, and calendar spreads. The remaining category of other strategies consists of any combinations of option contracts which do not fall into the above categories. For each strategy category, we report the number of account-days that hold a position corresponding to the strategy, as a percentage of all account-days with a non-zero end-of-day position in options. We also report the average percentage of open interest: for each strategy, first we calculate the end-of-day number of options held by all investors who use that strategy, as a percentage of the total number of options held in the market by all investors (overall open interest), and then we take the time-series average. The open interest percentages sum to a total of 200% since each option contract is held simultaneously by two counterparties – each long position has a corresponding short position. The table contains results for all account-days aggregated, as well as for each investor class separately. The sample time period is from 1 January 2010 to 30 June 2014.

	All		Domestic Institutions		Foreign Institutions		Domestic Retail		Foreign Retail	
Number of account-days with a non-zero position in options	19,135,324		409,754		129,926		18,521,112		74,532	
	% of above account-days	average % of open interest	% of above account-days	average % of open interest	% of above account-days	average % of open interest	% of above account-days	average % of open interest	% of above account-days	average % of open interest
Options and futures	6.24%	88.7%	25.4%	22.0%	63.0%	56.3%	5.42%	10.3%	7.27%	0.04%
Naked options	55.7%	14.6%	21.3%	0.72%	11.0%	0.95%	56.8%	12.9%	47.6%	0.06%
Volatility trading	16.5%	14.5%	11.1%	2.93%	4.03%	0.70%	16.7%	10.8%	17.7%	0.04%
Spreads	3.68%	5.91%	11.9%	2.74%	2.20%	0.21%	3.50%	2.95%	4.73%	0.02%
Other strategies	17.9%	76.3%	30.3%	17.6%	19.8%	13.3%	17.6%	45.0%	22.7%	0.36%

Table 5
Strategies of position holders: Combinations of options and futures

This table focuses on the strategies that option position holders create in combination with futures. We extract these by checking the type of options and futures exposure that an account-day has: long calls, short calls, long puts, short puts, long futures, or short futures. Long covered calls consist of long calls and short futures, while short covered calls consist of short calls and long futures. Long protective puts are created with long puts and long futures, while short protective puts are created with short puts and short futures. The table breaks down the category of options-and-futures combinations into these four strategies, as well as a remaining category of any other combinations. For each sub-category, we report the number of account-days that hold a position corresponding to the strategy, as a percentage of all account-days with a non-zero end-of-day position in options. We also report the average percentage of open interest: for each strategy, first we calculate the end-of-day number of options held by all investors who use that strategy, as a percentage of the total number of options held in the market by all investors (overall open interest), and then we take the time-series average. The total open interest in the market sums to 200% since each option contract is held simultaneously by two counterparties – each long position has a corresponding short position. The table contains results for all account-days aggregated, as well as for each investor class separately. The sample time period is from 1 January 2010 to 30 June 2014.

	All		**Domestic Institutions**		**Foreign Institutions**		**Domestic Retail**		**Foreign Retail**	
Number of account-days with a non-zero position in options	19,135,324		409,754		129,926		18,521,112		74,532	
	% of above account-days	average % of open interest	% of above account-days	average % of open interest	% of above account-days	average % of open interest	% of above account-days	average % of open interest	% of above account-days	average % of open interest
Options and futures	6.24%	88.7%	25.4%	22.0%	63.0%	56.3%	5.42%	10.3%	7.27%	0.04%
● long covered calls	0.21%	0.20%	0.32%	0.02%	0.85%	0.10%	0.21%	0.08%	0.28%	0.00%
● short covered calls	0.28%	0.43%	1.71%	0.13%	0.21%	0.00%	0.25%	0.30%	0.42%	0.00%
● long protective puts	0.24%	0.31%	0.45%	0.04%	2.46%	0.19%	0.22%	0.08%	0.73%	0.00%
● short protective puts	0.25%	0.28%	0.99%	0.05%	0.47%	0.02%	0.23%	0.21%	0.47%	0.00%
● other combinations	5.26%	87.5%	21.9%	21.7%	59.0%	56.0%	4.51%	9.66%	5.38%	0.04%

Table 6
Strategies of position holders: Naked options in one type of position only

This table takes a closer look at naked options in one type of position only. We include here account-days which hold naked positions in either long calls only, or short calls only, or long puts only, or short puts only. These are one-directional exposures which are not combined with any positions in futures contracts. For each sub-category, we report the number of account-days that hold a position corresponding to the strategy, as a percentage of all account-days with a non-zero end-of-day position in options. We also report the average percentage of open interest: for each strategy, first we calculate the end-of-day number of options held by all investors who use that strategy, as a percentage of the total number of options held in the market by all investors (overall open interest), and then we take the time-series average. The total open interest in the market sums to 200% since each option contract is held simultaneously by two counterparties – each long position has a corresponding short position. The table contains results for all account-days aggregated, as well as for each investor class separately. The sample time period is from 1 January 2010 to 30 June 2014.

	All		Domestic Institutions		Foreign Institutions		Domestic Retail		Foreign Retail	
Number of account-days with a non-zero position in options	19,135,324		409,754		129,926		18,521,112		74,532	
	% of above account-days	average % of open interest	% of above account-days	average % of open interest	% of above account-days	average % of open interest	% of above account-days	average % of open interest	% of above account-days	average % of open interest
Naked options	55.7%	14.6%	21.3%	0.72%	11.0%	0.95%	56.8%	12.9%	47.6%	0.06%
• long call	30.2%	7.52%	4.12%	0.12%	2.04%	0.14%	31.0%	7.23%	22.3%	0.02%
• short call	2.04%	0.99%	8.09%	0.38%	0.57%	0.06%	1.92%	0.55%	2.44%	0.00%
• long put	21.3%	5.28%	5.42%	0.14%	8.04%	0.75%	21.8%	4.37%	19.6%	0.03%
• short put	2.17%	0.83%	3.68%	0.07%	0.36%	0.00%	2.14%	0.75%	3.36%	0.00%

Table 7
Strategies of position holders: Volatility trading

This table presents details about the different strategies that option position holders use to trade on underlying volatility. First, we extract long and short straddles and strangles created by taking a position in two different option contracts only. Long (short) straddles are created by combining long (short) calls and long (short) puts with the same strike price and maturity date. Long (short) strangles are created with long (short) calls and long (short) puts with the same maturity date but different strike prices. Next, we would like to extract account-days that use more than two different option contracts to create combinations of straddles and strangles. Regardless of how many different option contracts an account-day uses, we check the types of exposures they have. If they hold long calls and long puts only, we can be sure that they are using a combination of long straddles and/or long strangles. If they hold short calls and short puts only, then they are using a combination of short straddles and/or short strangles. In the table below, we report these strategies as “long combinations” and “short combinations”. Finally, we extract butterflies created with three different option contracts. A call (put) butterfly spread is a strategy that combines three call (put) contracts with different strike prices, such that the option contract with the middle strike price has twice the number of lots invested in it, compared to the number of lots invested in the other two option contracts. For example, a long call butterfly can be created by buying one lot in a call option contract with the lowest strike price, selling two lots in a call option contract with the middle strike price, and buying one lot in a call option contract with the highest strike price. We must note that we are only able to identify butterfly spreads created using three different option contracts, but we are unable to extract any combinations of butterflies created using six, nine, or more different option contracts, because we cannot be sure that they are not other strategies. Similarly, some combinations of long and short straddles and strangles may be left in the category of other strategies, because we cannot say for sure what type of strategy is used by an account that holds a large number of different option contracts. Therefore, the numbers presented in this table are lower bounds, and the usage of options for volatility trading may in fact be larger.

For each sub-category, we report the number of account-days that hold a position corresponding to the strategy, as a percentage of all account-days with a non-zero end-of-day position in options. We also report the average percentage of open interest: for each strategy, first we calculate the end-of-day number of options held by all investors who use that strategy, as a percentage of the total number of options held in the market by all investors (overall open interest), and then we take the time-series average. The total open interest in the market sums to 200% since each option contract is held simultaneously by two counterparties – each long position has a corresponding short position. The table contains results for all account-days aggregated, as well as for each investor class separately. The sample time period is from 1 January 2010 to 30 June 2014.

	All		Domestic Institutions		Foreign Institutions		Domestic Retail		Foreign Retail	
Number of account-days with a non-zero position in options	19,135,324		409,754		129,926		18,521,112		74,532	
	% of above account-days	average % of open interest	% of above account-days	average % of open interest	% of above account-days	average % of open interest	% of above account-days	average % of open interest	% of above account-days	average % of open interest
Volatility trading	16.5%	14.5%	11.1%	2.93%	4.03%	0.70%	16.7%	10.8%	17.7%	0.04%
● long straddle	0.18%	0.03%	0.04%	0.00%	0.04%	0.00%	0.18%	0.03%	0.22%	0.00%
● short straddle	0.20%	0.05%	0.50%	0.00%	0.19%	0.01%	0.19%	0.03%	0.29%	0.00%
● long strangle	4.67%	1.04%	0.70%	0.02%	0.46%	0.03%	4.79%	0.98%	3.70%	0.00%
● short strangle	2.56%	2.10%	1.93%	0.24%	0.23%	0.01%	2.59%	1.85%	3.94%	0.01%
● long combinations	3.44%	2.12%	0.98%	0.68%	1.29%	0.17%	3.52%	1.28%	2.59%	0.01%
● short combinations	5.37%	9.11%	6.87%	1.98%	1.74%	0.49%	5.36%	6.63%	6.89%	0.02%
● long call butterfly	0.01%	0.01%	0.03%	0.00%	0.02%	0.00%	0.01%	0.00%	0.01%	0.00%
● short call butterfly	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
● long put butterfly	0.02%	0.02%	0.09%	0.01%	0.05%	0.00%	0.02%	0.01%	0.01%	0.00%
● short put butterfly	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%

Table 8
Possible market makers

In this table, we attempt to identify account-days whose behavior resembles that of market makers. These are account-days that hold complex combinations of multiple different contracts, which do not correspond to any other trading strategy, and have low delta and vega exposure. We start by collecting account-days which have remained without an assigned strategy. These include the account-days holding combinations of options and futures other than covered calls and protective puts (reported as "other combinations" in the last row of Table 5). They also include account-days holding only options, whose strategies do not include naked options, volatility trading, or spreads (reported as "other strategies" in the last row of Table 4). From these, we exclude any positions which may be used to achieve a calendar exposure (combinations of options with different maturities). We are left with complex strategies using more than two different option contracts, with more than two different exposures out of the four possible ones: long calls, short calls, long puts, and short puts. Hence, we identify a set of account-days which we refer to as possible market makers, reported in the first row of the table. In order to separate the market makers from any volatility traders, we impose artificial cut-offs on the greeks exposure of these account-days. We calculate the 50th and the bottom 25th percentiles of absolute scaled delta exposure and absolute scaled vega exposure of this sub-sample of possible market makers. Those account-days that are in both the bottom delta percentile and the bottom vega percentile are categorized as market makers. The table below reports the results for both cases when we use 50% and 25% as the cut-off. For each sub-sample, we report the number of account-days as a percentage of all account-days with a non-zero end-of-day position in options. We also report the average percentage of open interest: first we calculate the end-of-day number of options held by all investors in the sub-sample, as a percentage of the total number of options held in the market by all investors (overall open interest), and then we take the time-series average. The total open interest in the market sums to 200% since each option contract is held simultaneously by two counterparties – each long position has a corresponding short position. The table contains results for all account-days aggregated, as well as for each investor class separately. The sample time period is from 1 January 2010 to 30 June 2014.

	All		Domestic Institutions		Foreign Institutions		Domestic Retail		Foreign Retail	
Number of account-days with a non-zero position in options	19,135,324		409,754		129,926		18,521,112		74,532	
	% of above account-days	average % of open interest	% of above account-days	average % of open interest	% of above account-days	average % of open interest	% of above account-days	average % of open interest	% of above account-days	average % of open interest
Possible market makers	22.2%	163.6%	52.0%	39.4%	78.7%	69.4%	21.2%	54.5%	27.1%	0.39%
● greeks in bottom 50%	7.08%	77.2%	20.5%	20.7%	23.3%	27.8%	6.66%	28.6%	10.2%	0.28%
● greeks in bottom 25%	2.29%	38.0%	10.3%	14.4%	9.85%	12.6%	2.06%	11.1%	3.01%	0.18%

Table 9
Strategies by account

Table 9 reports the number of accounts for each strategy and each investor class, as well as the percentage of total trading volume over the sample period that the group has generated. The total number of accounts in the sample is 187,323. We label each account as day trader, naked options trader, volatility trader, market maker, or other. Day traders are defined as accounts that never hold a position at the end of the trading day. The rest of the accounts, which are position holders, may hold different strategies on different days throughout the sample period. For this reason, we define an account as a naked options trader only if he holds naked options positions on at least 50% of the days when he holds any non-zero position in options. Similarly, we mark an account as a volatility trader (market maker) if he holds positions that correspond to a volatility trading (market making) strategy at least 50% of all days when he holds any options position. The remaining category labelled as “others” consists of accounts that engage in other options strategies most of the time, accounts that use several different strategies without having a predominant one, and accounts that trade only futures but not options. The table contains results for all accounts aggregated, as well as for each investor class separately. The sample time period is from 1 January 2010 to 30 June 2014.

	All	Domestic Institutions	Foreign Institutions	Domestic Retail	Foreign Retail
	Number of accounts (% of total volume)	Number of accounts (% of total volume)	Number of accounts (% of total volume)	Number of accounts (% of total volume)	Number of accounts (% of total volume)
Day traders	13,587	1,252	77	12,204	54
	10.6%	7.2%	2.2%	1.2%	0.0%
Naked options traders	103,541	1,091	159	101,958	333
	38.2%	8.4%	9.3%	20.5%	0.1%
Volatility traders	10,396	267	15	10,067	47
	4.9%	0.5%	0.9%	3.5%	0.0%
Market makers	4,873	548	101	4,188	36
	21.1%	5.5%	13.7%	1.8%	0.0%
Others	54,926	10,637	1,204	42,857	228
	25.2%	10.7%	7.7%	6.7%	0.0%

Table 10
Profitability of the different types of option trading accounts and strategies

This table presents regression analyses of the relation between profitability and investor types. The total number of investor accounts in the sample is 187,323. For each account, we use the transactions records to calculate the total cumulative profit and loss (P&L) over the whole sample period. Hence, our measure of account profitability is the dollar amount generated by all trades that the account has executed from 1 January 2010 to 30 June 2014. If there are any positions that are not closed before the end of our sample period, we mark them to market based on the closing value of the underlying index on the last trading day in our sample. We perform four account-level regression analyses. The dependent variable in all of them is the logarithmic transformation of account P&L. If an account has generated a positive profit over the sample period, we calculate *log(1+P&L)*. If an account has generated a loss instead, we calculate *log(1/(1– P&L))*. The table contains the estimated regression coefficients and below them the corresponding t-statistics in parentheses.

The independent variables in the first regression are three dummy variables for the three investor classes: foreign retail, domestic institution, and foreign institution. Since all the remaining accounts are domestic retail, the intercept represents that class of investors. The second regression uses as independent variables four dummies for the four types of option traders we identified: day traders, naked option traders, volatility traders, and market makers. The third regression adds interaction effects between the strategy dummies and the investor class dummies. The fourth regression adds control variables for account activity. We calculate each account's total trading volume generated over the whole sample period (all the trades that he executed in order to generate his cumulative P&L), as well as the number of days in the sample when the account was active (the number of days when he traded options or futures at least once). We take the logarithms of these variables.

Dependent variable: log transformation of P&L

	1	2	3	4
Intercept	-8.330	-3.614	-4.899	-1.495
	(-253.1)	(-63.56)	(-76.78)	(-14.45)
Foreign retail	2.307		0.810	0.831
	(4.47)		(0.92)	(0.95)
Domestic institution	9.645		5.889	5.240
	(80.00)		(41.16)	(36.37)
Foreign institution	10.987		6.403	6.488
	(31.67)		(16.59)	(16.86)
Day trader		-0.355	0.169	-0.522
		(-2.78)	(1.25)	(-3.72)
Naked options trader		-7.314	-6.159	-5.734
		(-104.0)	(-81.01)	(-74.14)
Volatility trader		0.314	1.372	1.746
		(2.20)	(9.38)	(11.96)
Market maker		5.590	5.815	6.753
		(28.06)	(27.19)	(31.51)
Day trader * Foreign retail			2.895	2.550
			(1.44)	(1.28)
Day trader * Domestic institution			1.192	3.503
			(2.86)	(8.37)
Day trader * Foreign institution			9.954	12.782
			(6.39)	(8.23)
Naked options trader * Foreign retail			-0.567	-0.619
			(-0.50)	(-0.55)
Naked options trader * Domestic institution			4.872	5.580
			(11.42)	(13.13)
Naked options trader * Foreign institution			3.411	4.016
			(3.05)	(3.61)
Volatility trader * Foreign retail			4.242	4.219
			(2.00)	(2.00)
Volatility trader * Domestic institution			1.638	2.536
			(1.97)	(3.06)
Volatility trader * Foreign institution			0.825	1.969
			(0.24)	(0.58)
Market maker * Foreign retail			6.963	6.956
			(2.93)	(2.94)
Market maker * Domestic institution			0.329	2.041
			(0.53)	(3.31)
Market maker * Foreign institution			8.219	10.335
			(5.94)	(7.49)
log (Total account trading volume)				-0.445
				(-24.44)
log (Account active days)				-0.086
				(-2.78)
N observations	187,323	187,323	187,323	187,323
Adjusted R^2	0.037	0.079	0.095	0.104

Table 11
Relation between account profitability and greeks exposure

This table shows the relation between account profitability and exposure to the greeks. We calculate each account's end-of-day delta and vega exposure, scaled by the number of lots held by the account on that day. Then, we take the time-series average of the account's long delta exposure, absolute short delta exposure, long vega exposure, and absolute short vega exposure. Since day traders do not hold any overnight positions and therefore do not have any end-of-day greeks exposure, we exclude them from this analysis. The number of observations is further reduced because we have missing values for some accounts' exposure to the greeks (there are instances when it is not possible to estimate end-of-day delta and vega). We perform three account-level regression analyses. The dependent variable in all of them is the logarithmic transformation of account P&L (calculated in the same way as in Table 10). The table contains the estimated regression coefficients and below them the corresponding t-statistics in parentheses. The sample time period is from 1 January 2010 to 30 June 2014.

The independent variables in the first regression are average long delta and vega exposure, and average absolute short delta and vega exposure. The second regression adds the three investor class dummies, as well as interaction effects between the greeks exposure variables and the investor class dummies. The third regression adds control variables for account activity: logarithm of total account trading volume and logarithm of account active days (calculated in the same way as in Table 10).

Dependent variable: log transformation of P&L

	1	2	3
Intercept	-6.312	-7.086	-2.503
	(-92.60)	(-101.9)	(-19.76)
Average long delta exposure	-2.269	-2.751	-2.445
	(-7.90)	(-9.26)	(-8.27)
Average absolute short delta exposure	-0.766	-2.436	-2.520
	(-2.55)	(-7.76)	(-8.08)
Average long vega exposure	-0.335	-0.249	-0.233
	(-45.57)	(-32.52)	(-30.58)
Average absolute short vega exposure	0.266	0.277	0.303
	(45.91)	(47.32)	(51.26)
Foreign retail		5.830	5.969
		(5.66)	(5.83)
Domestic institution		12.041	13.547
		(34.57)	(38.76)
Foreign institution		15.268	18.219
		(17.36)	(20.75)
Average long delta exposure * Foreign retail		-2.415	-1.841
		(-0.49)	(-0.38)
Average absolute short delta exposure * Foreign retail		1.272	1.321
		(0.27)	(0.28)
Average long vega exposure * Foreign retail		-0.417	-0.447
		(-3.69)	(-3.97)
Average absolute short vega exposure * Foreign retail		-0.100	-0.106
		(-1.09)	(-1.17)
Average long delta exposure * Domestic institution		0.702	-2.196
		(0.62)	(-1.95)
Average absolute short delta exposure * Domestic institution		0.992	-1.256
		(0.88)	(-1.12)
Average long vega exposure * Domestic institution		-0.366	-0.357
		(-9.75)	(-9.57)
Average absolute short vega exposure * Domestic institution		-0.220	-0.289
		(-6.58)	(-8.70)
Average long delta exposure * Foreign institution		4.537	5.052
		(1.18)	(1.33)
Average absolute short delta exposure * Foreign institution		-5.352	-6.349
		(-1.35)	(-1.62)
Average long vega exposure * Foreign institution		-0.303	-0.425
		(-3.65)	(-5.14)
Average absolute short vega exposure * Foreign institution		-0.187	-0.201
		(-1.72)	(-1.86)
log (Total account trading volume)			-0.583
			(-28.10)
log (Account active days)			-0.043
			(-1.21)
N observations	144,602	144,602	144,602
Adjusted R^2	0.040	0.059	0.071

Table 12
Skewness of daily, weekly, and monthly account profitability

This table presents regression analyses of the relation between investor types and skewness of daily, weekly, and monthly profitability. The total number of investor accounts in the sample is 187,323. For each account, we use the transactions records to calculate profit and loss (P&L) on daily, weekly, and monthly horizons. Hence, the measure of profitability here is the dollar amount generated by all trades that the account has executed on each day, week, or month. If there are any positions that are not closed before the end of the horizon, we mark them to market based on the closing value of the underlying index at the end of the given day, week, or month. We apply a logarithmic transformation to the calculated daily, weekly, and monthly P&L values in the following way. If an account has generated a positive profit, we calculate log(1+P&L). If an account has generated a loss instead, we calculate log(1/(1– P&L)). Then, for each account, we calculate the skewness of his daily, weekly, and monthly profitability over the sample period. The sample time period is from 1 January 2010 to 30 June 2014.

We perform three regression analyses, where the dependent variables are skewness of daily log P&L, skewness of weekly log P&L, and skewness of monthly log P&L. The independent variables in all of them are the same as in Table 10. The results report the estimated regression coefficients and below them the corresponding t-statistics in parentheses.

	Dependent variable:		
	Skewness of daily log P&L	Skewness of weekly log P&L	Skewness of monthly log P&L
Intercept	-0.182	-0.059	-0.030
	(-51.08)	(-12.80)	(-4.35)
Foreign retail	0.041	-0.009	-0.114
	(0.85)	(-0.14)	(-1.22)
Domestic institution	0.028	-0.044	-0.155
	(3.34)	(-4.01)	(-9.69)
Foreign institution	0.132	0.018	0.010
	(5.83)	(0.62)	(0.25)
Day trader	0.027	0.236	0.420
	(3.17)	(20.01)	(21.93)
Naked options trader	0.276	0.519	0.958
	(65.35)	(94.39)	(118.3)
Volatility trader	-0.101	-0.107	-0.159
	(-12.44)	(-10.18)	(-10.28)
Market maker	-0.174	-0.415	-0.677
	(-14.90)	(-27.70)	(-31.03)
Day trader * Foreign retail	-0.382	-0.043	-0.096
	(-2.85)	(-0.24)	(-0.32)
Day trader * Domestic institution	-0.235	-0.421	-0.524
	(-9.63)	(-13.14)	(-10.76)
Day trader * Foreign institution	-1.404	-1.223	-1.113
	(-15.62)	(-10.65)	(-6.80)
Naked options trader * Foreign retail	-0.052	-0.074	-0.005
	(-0.82)	(-0.90)	(-0.04)
Naked options trader * Domestic institution	-0.389	-0.661	-0.979
	(-16.12)	(-20.99)	(-21.21)
Naked options trader * Foreign institution	-0.248	-0.531	-0.813
	(-3.81)	(-6.32)	(-6.95)
Volatility trader * Foreign retail	-0.290	-0.320	-0.467
	(-2.50)	(-2.14)	(-2.17)
Volatility trader * Domestic institution	-0.473	-0.307	-0.498
	(-10.36)	(-4.88)	(-5.55)
Volatility trader * Foreign institution	-0.512	-0.665	-0.560
	(-2.56)	(-2.63)	(-1.62)
Market maker * Foreign retail	-0.262	-0.160	-0.702
	(-2.03)	(-0.95)	(-2.94)
Market maker * Domestic institution	-0.055	-0.005	0.027
	(-1.62)	(-0.12)	(0.43)
Market maker * Foreign institution	-0.170	-0.369	-0.186
	(-2.22)	(-3.77)	(-1.33)
N observations	174,508	165,288	143,680
Adjusted R^2	0.046	0.093	0.153

Table 13
Out-of-sample performance persistence analysis

This table reports the in-sample and out-of-sample profitability of the different types of investors. We start by dividing our sample into two equal subperiods. The first half of the sample, used for in-sample analysis, covers the period from 1 January 2010 to 31 Mar 2012. The second half of the sample, used for out-of-sample analysis, covers the remaining period from 1 Apr 2012 until 30 June 2014. Using trading data only from the first half of the sample, we assign to each account a strategy dummy: naked options trader, volatility trader, or market maker. We create the dummies following the same principle as in previous analyses: for example, if an account uses a volatility trading strategy at least 50% of the time in-sample (50% of the days when he holds a position in-sample), then he is marked as a volatility trader. Then, we keep the same account classification for the second half of the sample. We only keep accounts that have transactions in both subperiods, which significantly reduces the sample. For each account, we calculate profits generated in the two subperiods (in-sample P&L and out-of-sample P&L), and we use a logarithmic transformation of P&L (calculated in the same way as in Table 10). We calculate excess log P&L, equal to log P&L minus market average log P&L. Finally, we report summary statistics for the calculated profitability measures. For each investor type, the table contains the number of accounts, in-sample and out-of-sample average excess log P&L, and the corresponding t-statistics in parentheses.

Investor type		N observations	In-sample mean excess log P&L	Out-of-sample mean excess log P&L
Naked options traders	Domestic retail	24,826	-3.45	-3.56
			(-44.61)	(-46.71)
	Foreign retail	78	-2.89	-2.78
			(-1.91)	(-1.90)
	Domestic institution	256	6.40	6.91
			(5.71)	(6.23)
	Foreign institution	38	4.50	9.86
			(1.33)	(3.11)
Volatility traders	Domestic retail	3,405	5.67	7.06
			(20.23)	(24.98)
	Foreign retail	13	8.38	4.56
			(1.72)	(0.95)
	Domestic institution	52	10.31	16.07
			(4.01)	(7.28)
	Foreign institution	3	23.52	12.75
			(21.73)	(1.24)
Market makers	Domestic retail	1,041	9.87	8.23
			(19.21)	(15.50)
	Foreign retail	10	9.79	15.30
			(1.79)	(2.72)
	Domestic institution	89	16.09	18.16
			(9.11)	(11.17)
	Foreign institution	31	17.15	10.01
			(5.33)	(2.58)